HW02WP_ML

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0.1 HW 2 Analysis Problems

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0.2 1. Data Wrangling, Pre-Processing I

Import datetime

[ ]:
```
from datetime import datetime as dt
now = dt.now()
print("Analysis on", now.strftime("%Y-%m-%d"), "at", now.strftime("%H:%M %p"))
```

```
Analysis on 2023-07-06 at 11:32 AM
```

Current working directory

[ ]:
```
import os
os.getcwd()
```

[ ]:
```
'/Users/chasecarlson/Documents/GSCM Course Materials/GSCM 575 Machine Learning
in Business/Python Pjojects/GSCM-575-ML/code'
```

Import packages

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Consider the following csv data file regarding houses and their average selling price in various geographical areas around Boston:

http://web.pdx.edu/~gerbing/data/Boston.csv

There are 14 variables in the data file, described as follows:

1. crim - per capita crime rate by town
2. zn - proportion of residential land zoned for lots over 25,000 sq.ft.
3. indus - proportion of non-retail business acres per town.
4. chas - charles river dummy variable (1 if tract bounds river; 0 otherwise)
5. nox - nitric oxides concentration (parts per 10 million)
6. rm - average number of rooms per dwelling

7. age - proportion of owner-occupied units built prior to 1940
8. dis - weighted distances to five boston employment centers
9. rad - index of accessibility to radial highways
10. tax - full-value property-tax rate per 10,000 USD
11. ptratio - pupil-teacher ratio by town
12. "b - 1000(bk - 0.63)^2" where bk is the proportion of blacks by town
13. lstat - % lower status of the population
14. medv - median value of owner-occupied homes in 1000's USD

a. Read the data file.

[ ]:
```
df = pd.read_csv("http://web.pdx.edu/~gerbing/data/Boston.csv")
df.head()
```

[ ]:
```
   Unnamed: 0     crim    zn  indus  chas    nox     rm   age     dis  rad  \
0           1  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1
1           2  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2
2           3  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2
3           4  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3
4           5  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3

   tax  ptratio   black  lstat  medv
0  296     15.3  396.90   4.98  24.0
1  242     17.8  396.90   9.14  21.6
2  242     17.8  392.83   4.03  34.7
3  222     18.7  394.63   2.94  33.4
4  222     18.7  396.90   5.33  36.2
```

The data frame imported with "unnamed column 0". Removing that column…

[ ]:
```
df = df.drop(columns=df.columns[0])
df
```

[ ]:
```
        crim    zn  indus  chas    nox     rm   age     dis  rad  tax  \
0    0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296
1    0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242
2    0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242
3    0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222
4    0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222
..       …     …     …    …     …     …     …       …  …    …
501  0.06263   0.0  11.93     0  0.573  6.593  69.1  2.4786    1  273
502  0.04527   0.0  11.93     0  0.573  6.120  76.7  2.2875    1  273
503  0.06076   0.0  11.93     0  0.573  6.976  91.0  2.1675    1  273
504  0.10959   0.0  11.93     0  0.573  6.794  89.3  2.3889    1  273
505  0.04741   0.0  11.93     0  0.573  6.030  80.8  2.5050    1  273

     ptratio   black  lstat  medv
0       15.3  396.90   4.98  24.0
1       17.8  396.90   9.14  21.6
```

```
2        17.8  392.83   4.03  34.7
3        18.7  394.63   2.94  33.4
4        18.7  396.90   5.33  36.2
..        …      …     …    …
501      21.0  391.99   9.67  22.4
502      21.0  396.90   9.08  20.6
503      21.0  396.90   5.64  23.9
504      21.0  393.45   6.48  22.0
505      21.0  396.90   7.88  11.9

[506 rows x 14 columns]
```

b. How many examples (rows of data) are there in the data file?

Check the shape of the data frame

[ ]:
```
df.shape
```

[ ]:
```
(506, 14)
```

c. List the first 5 rows and the variable names.

[ ]:
```
df.head()
```

[ ]:
```
      crim    zn  indus  chas    nox     rm   age     dis  rad  tax  ptratio  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296     15.3
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242     17.8
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242     17.8
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222     18.7
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222     18.7

    black  lstat  medv
0  396.90   4.98  24.0
1  396.90   9.14  21.6
2  392.83   4.03  34.7
3  394.63   2.94  33.4
4  396.90   5.33  36.2
```

d. Transform lstat *from a percentage to a proportion. Do this by writing the usual equation for this transformation in the language of Pandas, perhaps first writing the expression on paper and then translate to Pandas notation. (Name the new variable anything you wish.) Verify by displaying the first six rows of the revised data frame.*

Divide lstat % by 100 to transform into a proportion

[ ]:
```
df['lstat_prop'] = df['lstat']/100
df.head(6)
```

[ ]:
```
      crim    zn  indus  chas    nox     rm   age     dis  rad  tax  ptratio  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296     15.3
```

```
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242     17.8
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242     17.8
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222     18.7
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222     18.7
5  0.02985   0.0   2.18     0  0.458  6.430  58.7  6.0622    3  222     18.7

    black  lstat  medv  lstat_prop
0  396.90   4.98  24.0      0.0498
1  396.90   9.14  21.6      0.0914
2  392.83   4.03  34.7      0.0403
3  394.63   2.94  33.4      0.0294
4  396.90   5.33  36.2      0.0533
5  394.12   5.21  28.7      0.0521
```

e. Display just the average number of rooms for the second row of data.

Use iloc to find the single value from row 2 of 'rm' column.

[ ]:
```
df['rm'].iloc[1:2]
```

[ ]:
```
1    6.421
Name: rm, dtype: float64
```

f. To build a model to forecast median house price, analysts wish to focus on three predictor variables: crim, rm, and rad. Display the first five rows of data for just these three variables.
i. by specifying the variable names
ii. by specifying the variable indices

Filter the first five rows of crim, rm, and rad using filter().

[ ]:
```
df2 = df.filter(['crim', 'rm', 'rad'])
df2.head()
```

[ ]:
```
      crim     rm  rad
0  0.00632  6.575    1
1  0.02731  6.421    2
2  0.02729  7.185    2
3  0.03237  6.998    3
4  0.06905  7.147    3
```

Same thing using loc()

[ ]:
```
df2 = df.loc[:, ['crim', 'rm', 'rad']]
df2.head()
```

[ ]:
```
      crim     rm  rad
0  0.00632  6.575    1
1  0.02731  6.421    2
2  0.02729  7.185    2
3  0.03237  6.998    3
```

```
4  0.06905  7.147    3
```

Filter the first five rows of crim, rm, and rad by specifying the variable indices

[ ]:
```
df2 = df.iloc[:, [0, 5, 8]]
df2.head()
```

[ ]:
```
      crim     rm  rad
0  0.00632  6.575    1
1  0.02731  6.421    2
2  0.02729  7.185    2
3  0.03237  6.998    3
4  0.06905  7.147    3
```

g. List all the rows of data with the median value of the home less than $8000.

Filter all values in medv column less than 8 (in 1000s)

[ ]:
```
df.query('medv < 8')
```

[ ]:
```
         crim   zn  indus  chas    nox     rm    age     dis  rad  tax  \
385  16.81180  0.0  18.10     0  0.700  5.277   98.1  1.4261   24  666
387  22.59710  0.0  18.10     0  0.700  5.000   89.5  1.5184   24  666
398  38.35180  0.0  18.10     0  0.693  5.453  100.0  1.4896   24  666
399   9.91655  0.0  18.10     0  0.693  5.852   77.8  1.5004   24  666
400  25.04610  0.0  18.10     0  0.693  5.987  100.0  1.5888   24  666
401  14.23620  0.0  18.10     0  0.693  6.343  100.0  1.5741   24  666
405  67.92080  0.0  18.10     0  0.693  5.683  100.0  1.4254   24  666
414  45.74610  0.0  18.10     0  0.693  4.519  100.0  1.6582   24  666
415  18.08460  0.0  18.10     0  0.679  6.434  100.0  1.8347   24  666
416  10.83420  0.0  18.10     0  0.679  6.782   90.8  1.8195   24  666
489   0.18337  0.0  27.74     0  0.609  5.414   98.3  1.7554    4  711

     ptratio   black  lstat  medv  lstat_prop
385     20.2  396.90  30.81   7.2      0.3081
387     20.2  396.90  31.99   7.4      0.3199
398     20.2  396.90  30.59   5.0      0.3059
399     20.2  338.16  29.97   6.3      0.2997
400     20.2  396.90  26.77   5.6      0.2677
401     20.2  396.90  20.32   7.2      0.2032
405     20.2  384.97  22.98   5.0      0.2298
414     20.2   88.27  36.98   7.0      0.3698
415     20.2   27.25  29.05   7.2      0.2905
416     20.2   21.57  25.79   7.5      0.2579
489     20.1  344.05  23.97   7.0      0.2397
```

h. Use code (i.e., do not manually count) to display the number of homes with median value < $8000.

Count the number of homes with median value < 8

[ ]:
```
homes = df.query('medv < 8')['medv'].count()
print("Number of homes with medv < $8000: ", (homes))
```

```
Number of homes with medv < $8000:  11
```

i. Analysts want to build a model to forecast the median value of a house. Construct the box plot of the corresponding variable medv.

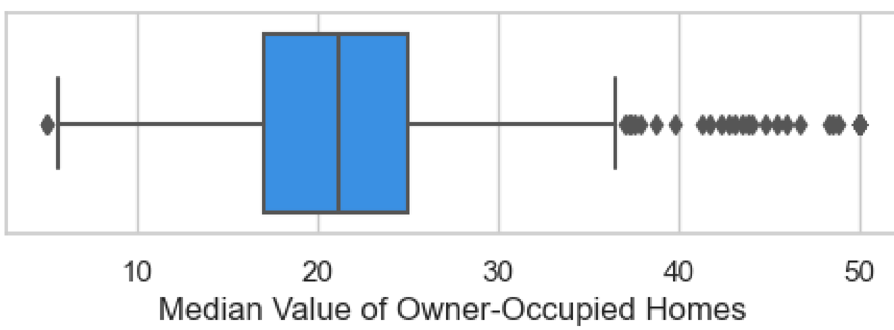
[ ]:
```
# Set plot theme
sns.set_theme(style='whitegrid')

# Use seaborn to create boxplot for the variable medv
plot = sns.boxplot(x=df['medv'], color='dodgerblue')

# Resize the figure
sns.set(rc={'figure.figsize': (6, 1.5)})

# Addd axis label
plot.set(xlabel='Median Value of Owner-Occupied Homes')
```

[ ]:
```
[Text(0.5, 0, 'Median Value of Owner-Occupied Homes')]
```



j. Describe the distribution of medv from the box plot including any outliers.

The data within the medv column is highly dispersed, with a range from 5-50. The mean is 22.53 and the median is 21.2. The middle 50% of values lie between 17 and 25, and the standard deviation is just over 9. There are a number of potential outliers with high values that skew the data to the right, and there is at least one potential outlier at the bottom end of the range.

[ ]:
```
round(df.describe()['medv'], 2)
```

[ ]:
```
count    506.00
mean      22.53
std        9.20
min        5.00
25%       17.02
```

```
50%        21.20
75%        25.00
max        50.00
Name: medv, dtype: float64
```

k. For the three predictor variables of interest, rescale into a data object called X three ways, each time showing the first five rows of rescaled data.
i. MinMax, and also show the minimum and maximum of the rescaled variables
ii. Standardize, and also show the mean and standard deviation of the rescaled variables and comment on their respective sizes
iii. Robust Scale

Pre-processing Import sklearn preprocessing module

[ ]:
```
from sklearn import preprocessing
```

View data types of predictor variables.

[ ]:
```
df[['crim', 'rm', 'rad']].dtypes
```

[ ]:
```
crim    float64
rm      float64
rad       int64
dtype: object
```

Subset the predictor variables (crim, rm, & rad) into their own data frame and update 'rad' to float64

[ ]:
```
X = df[['crim', 'rm', 'rad']].copy()
X.loc[:, 'rad'] = X.loc[:, 'rad'].astype('Float64')
X.head()
```

[ ]:

	crim	rm	rad
0	0.00632	6.575	1.0
1	0.02731	6.421	2.0
2	0.02729	7.185	2.0
3	0.03237	6.998	3.0
4	0.06905	7.147	3.0

i. Scale using MinMax Import MinMax Scaler and create mm_scaler instance

[ ]:
```
from sklearn.preprocessing import MinMaxScaler
mm_scaler = preprocessing.MinMaxScaler()
```

Transform X using MinMaxScaler and view object type

[ ]:
```
Xmm = mm_scaler.fit_transform(X)
type(Xmm)
```

[ ]: numpy.ndarray

Transform Xmm into a data frame and view first 5 rows

[ ]:
```
Xmm = pd.DataFrame(Xmm, columns=['crim', 'rm', 'rad'])
Xmm.head()
```

[ ]:
```
       crim        rm       rad
0  0.000000  0.577505  0.000000
1  0.000236  0.547998  0.043478
2  0.000236  0.694386  0.043478
3  0.000293  0.658555  0.086957
4  0.000705  0.687105  0.086957
```

View Min values

[ ]:
```
Xmm.min()
```

[ ]:
```
crim    0.0
rm      0.0
rad     0.0
dtype: float64
```

View Max values

[ ]:
```
Xmm.max()
```

[ ]:
```
crim    1.0
rm      1.0
rad     1.0
dtype: float64
```

ii. Scale using Standardization Import StandardScaler module and create instance

[ ]:
```
from sklearn.preprocessing import StandardScaler
s_scaler = preprocessing.StandardScaler()
```

Transform using Standard Scaler and convert back to data frame

[ ]:
```
Xst = s_scaler.fit_transform(X)
Xst = pd.DataFrame(Xst, columns=['crim', 'rm', 'rad'])
Xst.head()
```

[ ]:
```
       crim        rm       rad
0 -0.419782  0.413672 -0.982843
1 -0.417339  0.194274 -0.867883
2 -0.417342  1.282714 -0.867883
3 -0.416750  1.016303 -0.752922
4 -0.412482  1.228577 -0.752922
```

View the mean

[ ]:
```
round(Xst.mean(), 4)
```

[ ]:
```
crim   -0.0
rm     -0.0
rad    -0.0
dtype: float64
```

View standard deviation

[ ]:
```
round(Xst.std(), 4)
```

[ ]:
```
crim    1.001
rm      1.001
rad     1.001
dtype: float64
```

The mean of 0 and standard deviation of 1 represents a normal distribution of data. This ensures that the distribution of the data points is similar across different variables.

iii. Robust Scale Import RobustScaler module and create instance

[ ]:
```
from sklearn.preprocessing import RobustScaler
r_scaler = preprocessing.RobustScaler()
```

Transform X using RobustScaler and convert back to data frame

[ ]:
```
Xrb = r_scaler.fit_transform(X)
Xrb = pd.DataFrame(Xrb, columns=['crim', 'rm', 'rad'])
Xrb.head()
```

[ ]:

	crim	rm	rad
0	-0.069593	0.496612	-0.20
1	-0.063755	0.287940	-0.15
2	-0.063760	1.323171	-0.15
3	-0.062347	1.069783	-0.10
4	-0.052144	1.271680	-0.10

View the mean

[ ]:
```
round(Xrb.mean(), 4)
```

[ ]:
```
crim    0.9338
rm      0.1032
rad     0.2275
dtype: float64
```

View the standard deviation

```
[ ]: round(Xrb.std(), 4)
```

```
[ ]: crim    2.3926
     rm      0.9521
     rad     0.4354
     dtype: float64
```

View min

```
[ ]: round(Xrb.min(), 4)
```

```
[ ]: crim   -0.0696
     rm     -3.5874
     rad    -0.2000
     dtype: float64
```

View max

```
[ ]: round(Xrb.max(), 4)
```

```
[ ]: crim    24.6784
     rm       3.4844
     rad      0.9500
     dtype: float64
```

0.3 2. Data Wrangling, Pre-Processing II

Data: http://web.pdx.edu/~gerbing/data/SupermarketTransactions.xlsx (sample data from Tableau)

Read in the data

```
[ ]: supermarket = pd.read_excel('http://web.pdx.edu/~gerbing/data/
      ↪SupermarketTransactions.xlsx')
     supermarket.head()
```

```
[ ]:    Transaction   Purchase  Customer Gender Marital Homeowner  Children  \
     0            1 2015-12-17      7223      F       S         Y         2
     1            2 2015-12-19      7841      M       M         Y         5
     2            3 2015-12-20      8374      F       M         N         2
     3            4 2015-12-20      9619      M       M         Y         3
     4            5 2015-12-21      1900      F       S         Y         3

                Income           City State Country Family         Dept  \
     0    $30K - $50K    Los Angeles    CA     USA   Food  Snack Foods
     1    $70K - $90K    Los Angeles    CA     USA   Food      Produce
     2    $50K - $70K      Bremerton    WA     USA   Food  Snack Foods
     3    $30K - $50K       Portland    OR     USA   Food       Snacks
     4  $130K - $150K  Beverly Hills    CA     USA  Drink    Beverages
```

```
               Category  Units_Sold  Revenue
0           Snack Foods           5    27.38
1            Vegetables           5    14.90
2           Snack Foods           3     5.52
3                 Candy           4     4.44
4  Carbonated Beverages           4    14.00
```

a. *How many examples, rows of data? Columns of data?*

View the shape of the data frame

[ ]:
```
supermarket.shape
```

[ ]:
```
(14059, 16)
```

b. *Convert the value of Country, USA, to USofA. Verify. (Always verify the data after a transformation.)*

Replace USA with USofA targeting the 'Country' column

[ ]:
```
supermarket = supermarket.replace({'Country': {'USA': 'USofA'}})
supermarket.head()
```

[ ]:
```
   Transaction    Purchase  Customer Gender Marital Homeowner  Children  \
0            1 2015-12-17      7223      F       S         Y         2
1            2 2015-12-19      7841      M       M         Y         5
2            3 2015-12-20      8374      F       M         N         2
3            4 2015-12-20      9619      M       M         Y         3
4            5 2015-12-21      1900      F       S         Y         3

          Income           City State Country Family         Dept  \
0    $30K - $50K    Los Angeles    CA   USofA   Food  Snack Foods
1    $70K - $90K    Los Angeles    CA   USofA   Food      Produce
2    $50K - $70K      Bremerton    WA   USofA   Food  Snack Foods
3    $30K - $50K       Portland    OR   USofA   Food       Snacks
4  $130K - $150K  Beverly Hills    CA   USofA  Drink    Beverages

               Category  Units_Sold  Revenue
0           Snack Foods           5    27.38
1            Vegetables           5    14.90
2           Snack Foods           3     5.52
3                 Candy           4     4.44
4  Carbonated Beverages           4    14.00
```

c. *Identify the three countries in the data for the cateogrical variable Country.*

Finding unique values for Country. Countries include USofA, Mexico, and Canada

[ ]:
```
supermarket['Country'].unique()
```

[ ]:
```
array(['USofA', 'Mexico', 'Canada'], dtype=object)
```

d. *Sales took place in three countries. Convert the categorical variable Country to dummy variables for later numerical processing. What country gets dropped in the conversion?*

Use pd.get_dummies to create dummy variables for Country. Canada gets dropped because it is alphabetically first.

[ ]:
```python
supermarket = pd.get_dummies(supermarket, columns=['Country'], drop_first=True)
supermarket.head()
```

[ ]:
```
   Transaction   Purchase  Customer Gender Marital Homeowner  Children  \
0            1 2015-12-17      7223      F       S         Y         2
1            2 2015-12-19      7841      M       M         Y         5
2            3 2015-12-20      8374      F       M         N         2
3            4 2015-12-20      9619      M       M         Y         3
4            5 2015-12-21      1900      F       S         Y         3

         Income            City State Family         Dept  \
0    $30K - $50K    Los Angeles    CA   Food  Snack Foods
1    $70K - $90K    Los Angeles    CA   Food      Produce
2    $50K - $70K      Bremerton    WA   Food  Snack Foods
3    $30K - $50K       Portland    OR   Food       Snacks
4  $130K - $150K  Beverly Hills    CA  Drink    Beverages

               Category  Units_Sold  Revenue  Country_Mexico  Country_USofA
0           Snack Foods           5    27.38               0              1
1            Vegetables           5    14.90               0              1
2           Snack Foods           3     5.52               0              1
3                 Candy           4     4.44               0              1
4  Carbonated Beverages           4    14.00               0              1
```

0.4 3. Missing Data

Data: http://web.pdx.edu/~gerbing/data/employee.xlsx

Read in the data

[ ]:
```python
emp = pd.read_excel('http://web.pdx.edu/~gerbing/data/employee.xlsx')
emp.head()
```

[ ]:
```
               Name  Years Gender  Dept     Salary JobSat  Plan  Pre  Post
0  Ritchie, Darnell    7.0      M  ADMN   53788.26    med     1   82    92
1         Wu, James    NaN      M  SALE   94494.58    low     1   62    74
2       Hoang, Binh   15.0      M  SALE  111074.86    low     3   96    97
3     Jones, Alissa    5.0      W   NaN   53772.58    NaN     1   65    62
4    Downs, Deborah    7.0      W  FINC   57139.90   high     2   90    86
```

a. How many examples (rows of data) are there in the data file?

View the shape of the data frame

```
[ ]: emp.shape
```

```
[ ]: (37, 9)
```

b. Display rows of data that include the row of data with the missing data.

```
[ ]: emp[emp.isna().any(axis='columns')]
```

[ ]:

	Name	Years	Gender	Dept	Salary	JobSat	Plan	Pre	Post
1	Wu, James	NaN	M	SALE	94494.58	low	1	62	74
3	Jones, Alissa	5.0	W	NaN	53772.58	NaN	1	65	62
30	Korhalkar, Jessica	2.0	W	ACCT	72502.50	NaN	2	74	87

c. Impute the median for the missing data of Years employed at the company. (Verify, as always.)

Isolate the variable 'Years'

```
[ ]: X = emp.filter(['Years'])
     X.head()
```

[ ]:

	Years
0	7.0
1	NaN
2	15.0
3	5.0
4	7.0

Import SimpleImputer and create instance

```
[ ]: from sklearn.impute import SimpleImputer
     imp_med = SimpleImputer(missing_values=np.nan, strategy='median')
```

Fit to isolated variable and execute transformation

```
[ ]: imp_med = imp_med.fit(X)
     X = imp_med.transform(X)
```

Update data frame with missing values and verify result

```
[ ]: emp['Years'] = X
     emp.head()
```

[ ]:

	Name	Years	Gender	Dept	Salary	JobSat	Plan	Pre	Post
0	Ritchie, Darnell	7.0	M	ADMN	53788.26	med	1	82	92
1	Wu, James	9.0	M	SALE	94494.58	low	1	62	74
2	Hoang, Binh	15.0	M	SALE	111074.86	low	3	96	97
3	Jones, Alissa	5.0	W	NaN	53772.58	NaN	1	65	62
4	Downs, Deborah	7.0	W	FINC	57139.90	high	2	90	86

d. Display rows of data that include the row of data with the imputed data to verify that the missing data has been properly imputed to show the change from missing to the imputed median for each variable.

Display updated row for James Wu by targeting iloc

[ ]:
```
emp.iloc[1]
```

[ ]:
```
Name      Wu, James
Years           9.0
Gender            M
Dept           SALE
Salary     94494.58
JobSat          low
Plan              1
Pre              62
Post             74
Name: 1, dtype: object
```

View multiple rows that includes the updated value

[ ]:
```
emp.head()
```

[ ]:

	Name	Years	Gender	Dept	Salary	JobSat	Plan	Pre	Post
0	Ritchie, Darnell	7.0	M	ADMN	53788.26	med	1	82	92
1	Wu, James	9.0	M	SALE	94494.58	low	1	62	74
2	Hoang, Binh	15.0	M	SALE	111074.86	low	3	96	97
3	Jones, Alissa	5.0	W	NaN	53772.58	NaN	1	65	62
4	Downs, Deborah	7.0	W	FINC	57139.90	high	2	90	86